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Fake News, Investor Attention, and Market Reaction

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Abstract. Does fake news in financial markets attract more investor attention and have a significant impact on stock prices? We use the U.S. Securities and Exchange Commission (SEC) crackdown of stock promotion schemes in April 2017 to examine investor attention and the stock price reaction to fake news articles. Using data from Seeking Alpha, we find that fake news stories generate significantly more attention than a control sample of legitimate articles. We find no evidence that article commenters can detect fake news, and we also find that Seeking Alpha editors have only modest ability to detect fake news. However, we show that machine learning algorithms can successfully identify fake news from linguistic features of the article. The stock market appears to price fake news correctly. While abnormal trading volume increases around the release of fake news, the increase is less than that observed for legitimate news. The stock price reaction to fake news is discounted when compared with legitimate news articles.

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1. Introduction

Fake news has received considerable press attention in recent years. Facebook, Twitter, and other social media platforms have been criticized for promoting articles that later proved to be false. Based on anecdotal evidence, the reach of fake news stories is staggering. Facebook estimated that fake news stories about the 2016 election reached over 126 million Americans (Isaac and Wakabayashi 2017). Allcott and Gentzkow (2017) present evidence that half of those who recalled seeing fake news believed it. Moreover, they present additional evidence that education, age, and total media consumption are correlated with more accurate beliefs about the credibility of news headlines.

The real impact of fake news in financial markets is less well understood. In this paper, we first explore how fake news articles differ from legitimate news articles in the domain of financial markets. We then study the real impact of fake news articles by examining both investor attention and the stock market reaction to fake news articles. Our sample of fake news articles is obtained from the Securities and Exchange Commission (SEC) crackdown of several stock promotion schemes in April 2017. The SEC enforcement action covered 27 stock promoters who generated bullish articles about public companies under the guise of impartiality and independence. Undisclosed to market participants, the stock promoters were being compensated by companies to write the fake news stories. Many of the fake news articles were distributed on the website Seeking Alpha, which is one of the largest social media websites for financial markets in the world. Of the 27 stock promoters initially identified by the SEC, 17 agreed to pay settlements ranging from $2,200 to $3 million.

As an example of how these schemes worked, consider the case of Galena Biopharma, which traded under the ticker symbol GALE. GALE contracted with Lidingo Holdings to write a series of bullish articles on the company's stock. In one article appearing on March 21, 2012, Lidingo writer Brian Nichols wrote that, "The news of GALE being awarded a patent for NeuVax is huge, and will create opportunity long after the stock completes its three day rally. It's good news for just about everyone involved with this company and will create an unprecedented level of optimism among both the company and investors.” In the article, Nichols disclosed being long on GALE. In reality, Nichols purchased 1,000 shares of GALE just before his article was published on Seeking Alpha and sold the shares the day after his article appeared. Between 2011 and 2014, Lidingo received in excess of $1 million dollars in compensation for writing hundreds of fake news articles.

Previous research by Kirk (2011) finds that company-sponsored research contains value-relevant information. For firms in our fake news sample, however, the financial relationship between the research writer and the company was not disclosed. Disclosure of the compensation arrangement is required by Section 17(b) of the Securities Act of 1933.

From the SEC complaint, we identify all promotional articles that appeared on the website Seeking Alpha between August 1, 2011, and December 31, 2013. This sample consists of 383 fake news articles. We also have information on the 157,253 legitimate news articles published during the same time period on Seeking Alpha. For articles published between August 1, 2012, and March 31, 2013, we collect a proprietary data set from the company Seeking Alpha containing a number of data items relating to investor attention, including the number of times the article was viewed (i.e., page views), the number of distinct machine cookies that viewed the page, the number of times the article was read to the end, and the number of page views for which the comments were read. We also collect data on the number of comments received by each article and the content of each comment.

We have four primary results. First, relative to a control sample, fake news stories attract substantial investor attention. Page views, unique pages views, and the number of users who read the article to the end are all significantly higher for the sample of fake news articles. The results are economically meaningful. Fake news articles generate 83.4% more page views on average than legitimate news articles.

Second, we find that article commenters are unable to identify fake news stories. Fake news articles do not receive a significantly different number of comments compared with legitimate news articles. The level of contradiction between the sentiments revealed in the Seeking Alpha article and the comments it receives is not significantly greater for fake news articles relative to a control sample. We next examine whether Seeking Alpha editors are able to identify the fake news. Editors assign scores (on a four-point scale) across three dimensions to each article. The dimensions capture how convincing the article is (double weighted), how actionable the article is, and how well presented the article is. We find no economically meaningful evidence that editors assign lower scores to fake news articles. However, editors are 8.1% less likely to choose a fake news article as an editor pick.

Third, we implement several well-known machine learning algorithms based on linguistic characteristics for identifying fake news stories. Building on the literature that relies on linguistic styles to detect deception (e.g., Newman et al. 2003), we first demonstrate that there are statistically significant differences in 65 out of the total 93 output variables defined by the Linguistic Inquiry and Word Count (LIWC 2015) dictionary (Pennebaker et al. 1993, 2015) between the sample of fake news articles and its matched control sample of legitimate news articles. We then implement six classification algorithms including Gradient Boosting, Logistic Regression, Naïve Bayes, Neural Network, Random Forest, and Support Vector Machine based on the LIWC linguistic features. The gradient boosting classifier achieves the highest average F1 score of 88.7%. The other classification algorithms yield average F1 scores between 73.4% and 88.1%. Overall, these findings suggest that linguistic styles can be helpful in detecting fake news. Our results are consistent with Larcker and Zakolyukina (2012) showing that linguistic features can be used to detect deception by CEOs on conference calls.

Finally, we show that there is a significant increase in trading volume on the day a fake news article is released. However, the volume is less than that observed for legitimate articles. The magnitude of the stock price reaction to fake news articles is significantly less than a matched control sample over both short- and long-run windows surrounding the release of the fake news. Our results are robust to a number of different matching criteria.

Our findings are important to social media platforms, regulators, and investors. Our machine learning approach based on linguistic characteristics provides a method for social media platforms and regulators to identify attempts to manipulate the market by releasing fake news stories. For investors, our results suggest that fake news articles account for a small minority of articles on Seeking Alpha. Nonetheless, fake news stories attract significant investor attention. Article commenters and Seeking Alpha editors have limited ability to detect fake news articles. However, the market in aggregate is able to discern fake news. Both the trading volume and the absolute value of stock price reaction to fake news articles is statistically less than a matched control sample over short and long horizons.

A contemporaneous paper by Kogan et al. (2019) also examines the impact of fake news on financial markets. They find increases in trading volume and a temporary stock price reaction surrounding the release of fake news articles. They also find a decrease in fake content following the SEC’s crackdown on stock promotion schemes in 2017. Unlike Kogan et al. (2019), we can directly observe investor attention for our sample of fake news articles and also the editor scoring of fake news articles. We also have a more complete sample of fake news stories. Seeking Alpha pulled fake news articles from their website upon the SEC's announcement. The Kogan et al. study has only 171 fake news articles compared with our 383 fake news articles.[1]

The remainder of the paper proceeds as follows. Section 2 reviews prior literature related to fake news and presents our hypotheses. Section 3 discusses our data and defines the key variables used in the analyses. Section 4 presents our primary results. Section 5 concludes.

2. Literature Review and Hypothesis Development

In this section, we discuss the existing literature closely related to fake news in financial markets and present our hypotheses. Our discussion is broken down into three parts: (1) fake news and investor attention, (2) detecting fake news from linguistic features, and (3) the impact of fake news on trading volume and stock returns.

2.1. Fake News and Investor Attention

Research from nonfinancial markets suggests that fake news will attract more attention than legitimate news articles. Vosoughi et al. (2018), for example, examine the spread of true and fake rumors on Twitter. Their main finding is that fake news, especially fake political news, diffuses significantly faster and farther than legitimate news articles. The magnitude of the effect is large: their findings suggest that fake news is 70% more likely to be retweeted than legitimate news. Chopra et al. (2019) also provide experimental evidence that people have a demand for more biased news and that this demand is driven by a desire to confirm pre-existing beliefs. Using the optimal expectations model of Brunnermeier and Parker (2005) as a basis, Golman et al. (2017) suggest that people might rationally choose to avoid legitimate information as a means to maintain optimism. Since the majority of fake news articles in our sample involve a company paying a promotional firm to generate bullish articles, readers might be attracted to these bullish articles as a means of optimism maintenance. This leads to our first hypothesis.

Hypothesis 1. *Fake news articles will attract more investor attention than legitimate news articles.*

A key contribution of this study is to empirically test this relationship using a unique proprietary data set. Our data set allows us to precisely measure the change in investor attention around the release of fake news relative to a control sample of legitimate news articles.

2.2. Detecting Fake News Based on Linguistic Characteristics

A growing stream of literature in information systems, computer science, accounting, and finance examines the ability to detect deception using linguistics characteristics. Newman et al. (2003) find that liars communicate in qualitatively different ways than sincere storytellers. Liars tell stories that are less complex and less self-negative than truth tellers. Zhou and Zhang (2008) find that deceivers use more words and sentences; are more uncertain; and are more informal in their communications.

The information systems literature has examined the incidence and impact of fake product reviews. Hu et al. (2012) show that a textual analysis of sentiment and readability can be used to identify fake product reviews. Luca and Zervas (2016) examine fake reviews on Yelp and show that fake reviews tend to be more extreme than legitimate reviews. Fake reviews can have real consequences. Lappas et al. (2016) show that in certain markets as little as 50 fake reviews is sufficient for an attacker to surpass the visibility of its competitors.

In the context of financial markets, Larcker and Zakolyukina (2012) use textual analysis to predict deceptive discussions in earnings conference calls. Their findings suggest that deceptive executives have more references to general knowledge, use more positive emotion words and less anxiety words, and make fewer references to shareholder value. The authors' prediction model outperforms a random guessing strategy by 6% to 16%. Hobson et al. (2011) find that CEO speech patterns can also be used to detect accounting restatements. Purda and Skillicorn (2014) identify the words most strongly associated with deception in the management discussion and analysis sections of annual reports. This literature leads to our second testable hypothesis.

Hypothesis 2. *Fake news is detectable from linguistic features of the article.*

Prior research in psychology (e.g., Bond and DePaulo 2006, Vrij 2008) suggests that humans are not able to effectively detect deceptions and perform about as expected from random chance. Therefore, we first examine the ability of market commenters and Seeking Alpha editors to detect fake news. We then examine whether machine learning techniques can reliably detect fake news.

2.3. Fake News, Investor Attention, and Stock Market Reaction

Our final set of empirical tests examine the stock market reaction to fake news articles. We examine both abnormal volume and returns surrounding the announcement of fake news. With respect to trading volume, Kim and Verrecchia (1991) develop a theoretical model of trading and show that precision of news impacts the trading volume response. The more precise a piece of news, the more individuals revise their prior beliefs, which results in more trading. Several papers have found empirical support for the theoretical predictions of this model. For example, Bamber and Cheon (1995) find that trading volume is higher when earnings announcements generate divergent beliefs. Agrawal and Chen (2008) find that the abnormal volume reaction to conflicted sell-side analyst reports is lower than that of less conflicted research reports. Assuming that legitimate news articles are more precise than fake news articles, this leads to our third hypothesis.

Hypothesis 3. *Legitimate news articles will generate greater trading volumes than fake news articles.*

In a contemporaneous paper, Kogan et al. (2019) argue that in an informationally efficient market, fake news should have no impact on prices. Previous research suggests that markets are capable of discounting for biased information. For example, Agrawal and Chen (2008) find a smaller market reaction to the announcement of sell-side research reports issued by more biased analysts. To examine the information content of fake news versus legitimate news articles, we focus on the absolute value of the abnormal stock returns surrounding the release date. Cheon et al. (2001) and Bushee et al. (2010), among others, use the measure to examine the information content of earnings announcements. Therefore, our fourth hypothesis is as follows.

Hypothesis 4. *The absolute abnormal return to fake news articles will be less than legitimate news articles.*

3. Data and Variables

3.1. Fake News

We use the SEC's enforcement action issued on April 10, 2017 (Stempel 2017, U.S. Securities and Exchange Commission 2017), to identify fake news stories that were distributed on financial websites as part of stock promotion schemes. A list of 492 fake stock news articles is made publicly available by the SEC.[2] These articles were published from August 16, 2011, to March 10, 2014, on 13 different financial websites, among which Seeking Alpha (SA) had the largest number of fake news articles (412 out of 492). Seeking Alpha is one of the largest investment-related social media sites in the world and reported over 10 million unique visitors in 2018 (https://seekingalpha.com/page/who_reads_sa). The site relies on a crowd-sourced contributor network to publish opinion and analysis articles on a wide range of stocks. Prior research by Chen et al. (2014) shows that Seeking Alpha content contains value-relevant information for stock returns and earnings.

We obtained a proprietary data set from Seeking Alpha on 157,636 articles written by contributors between August 1, 2011, and December 31, 2013. Within this time period, we find 383 fake news articles covered by the SEC complaint.[3] For our analysis, we assume that all of the remaining 157,253 articles are legitimate. *Fake* is an indicator variable taking the value of 1 if the article was identified by the SEC as fake news, and 0 otherwise. Table 1 presents the summary statistics of all main variables for the groups of fake news articles (Panel A) and legitimate news articles (Panel B).

For each article, we have the following data: article id, title, main text, date of publication, author name, and list of stock tickers covered in the article. *Length* is the total number of words in an article. To measure the sentiment revealed in an article, we adopt the dictionary-based approach widely applied in the finance literature (e.g., Tetlock 2007, Tetlock et al. 2008, Chen et al. 2014) and use the negative word list developed by Loughran and McDonald (2011) specifically for financial markets. *%NegWord* is the fraction of negative words in an article in percentage points. *Premium* is an indicator variable denoting whether the author of the article receives monetary compensation from Seeking Alpha, which is determined mainly by the page views of the article. As shown in Table 1, compared with legitimate news articles, fake news articles are on average longer in length, less negative (i.e., more positive) in sentiment, and less likely to participate in Seeking Alpha's premium partnership program to receive monetary compensation.

3.2. Investor Attention

We also obtain a proprietary data set from Seeking Alpha on the attention received by all articles published from August 1, 2012, to March 31, 2013. This data set contains article-hourly level attention measures for 41,948 articles, 156 of which are fake news articles. The measures of attention include page views (*PVs*), the number of unique visitors (*Uniques*), the number of times an article was read to the end (*ReadToEnd*), and the number of page views for which the comments were read (*ReadComment*). Comparing between fake news and legitimate news articles, we find that, on average, fake news articles generate more page views, have a larger number of unique visitors, and are read to the end more often. However, the comments of fake news articles are, on average, read less often.

3.3. Commenter and Editor Reactions

To examine how SA commenters and editors may react to fake news and legitimate articles differently,

Table 1. Descriptive Statistics

Variable	Number of observations	Median	Mean	Standard deviation	Minimum	Maximum
			Panel A: Fake news articles			
Length	383	1,750	1,753.4	625.0	423	4,521
%NegWord	383	0.99	1.07	0.51	0	4.28
Premium	383	0	0.41	0.49	0	1
PVs	156	3,607.5	4,041.4	2,670.3	377	13,875
Uniques	156	3,296.5	3,595.4	2,358.3	338	12,517
ReadToEnd	156	1,355.5	1,667.0	1,135.9	112	5,963
ReadComment	156	0	79.5	159.2	0	869
Comment	383	7	11.2	11.9	0	79
%Contradiction	358	0.54	0.69	0.68	0	5.84
EditorPick	383	0	0.050	0.22	0	1
ConvincingScore	268	3	3.13	0.33	3	4
ActionableScore	268	3	3.17	0.38	3	4
WellPresentedScore	268	3	3.19	0.40	2	4
AggregateScore	268	3	3.18	0.38	3	4
$ARet_{0,1}$	346	0.0078	0.022	0.10	–0.23	0.65
$ARet_{0,2}$	346	0.0034	0.027	0.13	–0.25	0.72
$ARet_{3,120}$	346	–0.062	0.018	0.45	–0.77	1.89
$ARet_{3,242}$	346	–0.14	–0.0055	0.55	–0.85	2.06
$ARet_{-30,-1}$	346	0.031	0.12	0.35	–0.49	1.49
$AVol_{0,1}$	322	1.022	1.197	0.642	0.272	3.959
$AVol_{0,2}$	322	1.306	1.461	0.665	0.408	4.097
$AVol_{3,120}$	322	4.885	4.905	0.237	4.400	6.037
$AVol_{3,242}$	322	5.579	5.592	0.148	5.305	6.233
PosEA	383	0	0	0	0	0
NegEA	383	0	0.005	0.072	0	1
%NegFactiva	383	0	0.158	0.440	0	2.715
Factiva	383	0	0.261	0.440	0	1
Size	357	35.6	41.3	29.8	1.66	126.9
Market-to-Book	357	2.19	–20.3	83.5	–335.7	19.5
ROA	357	–0.66	–3.47	15.8	–114.1	–0.19
LEV	357	0.56	8.90	54.2	0.27	391.3
			Panel B: Legitimate news articles			
Length	157,253	861	1,008.1	668.1	100	16,325
%NegWord	157,253	1.27	1.48	1.05	0	14.7
Premium	157,253	1	0.65	0.48	0	1
PVs	41,792	1,886	2,954.7	4,167.2	1	447,869
Uniques	41,792	1,706	2,646.8	3,771.1	1	432,365
ReadToEnd	41,792	885	1,399.8	1,887.5	0	193,814
ReadComment	41,792	0	116.7	348.9	0	31,022
Comment	157,253	4	14.6	33.5	0	1,202
%Contradiction	124,760	0.69	0.96	1.19	0	99.0
EditorPick	157,253	0	0.045	0.21	0	1
ConvincingScore	91,365	3	3.11	0.32	1	4
ActionableScore	91,365	3	3.13	0.34	1	4
WellPresentedScore	91,365	3	3.22	0.42	1	4
AggregateScore	91,365	3	3.14	0.36	1	4
$ARet_{0,1}$	51,051	0.00011	0.0011	0.056	–0.85	2.46
$ARet_{0,2}$	51,051	–0.00017	0.00099	0.064	–0.86	2.13
$ARet_{3,120}$	51,051	–0.023	–0.010	0.32	–1.11	16.3
$ARet_{3,242}$	51,051	–0.047	–0.016	0.47	–1.30	8.02
$ARet_{-30,-1}$	51,051	–0.0049	0.0026	0.18	–0.91	5.85
$AVol_{0,1}$	49,900	1.090	1.179	0.444	0	6.429
$AVol_{0,2}$	49,900	1.380	1.461	0.450	0	6.444
$AVol_{3,120}$	49,900	4.783	4.799	0.175	0.716	8.043
$AVol_{3,242}$	49,900	5.489	5.504	0.162	0.716	8.281
PosEA	157,253	0	0.012	0.108	0	1
NegEA	157,253	0	0.004	0.066	0	1
%NegFactiva	248	0	0.047	0.300	0	3.448

Table 1. (Continued)

Variable	Number of observations	Median	Mean	Standard deviation	Minimum	Maximum
Factiva	248	0	0.331	0.471	0	1
Size	54,746	9,273.8	57,682.9	110,235.6	0.0055	626,550.4
Market-to-Book	54,746	2.64	6.41	61.9	−4,027.2	3,141.5
ROA	54,746	0.058	0.037	3.85	−182.2	198.7
LEV	54,746	0.53	0.60	3.36	0	391.3

and in particular whether SA commenters and editors would be able to detect fake news, we construct several measures to assess their reactions to SA articles.

Comment is the total number of comments received by an article. Although the number of comments is often positively correlated with the number of page views, the number of comments reveals the level of discussions around an article by the community. For the articles that receive at least one comment, *%Contradiction* is defined as the absolute difference between the fraction of negative words in the article and the average fraction of negative words across all comments received by the article (in percentage points). This variable is intended to measure whether commenters have different views from those expressed in an article.

EditorPick is an indicator variable denoting whether the article is featured in the Editors' Picks section. Starting from June 20, 2012, editors at Seeking Alpha assign scores (on a scale of 1–4) to each article along several dimensions. *ConvincingScore* is designed to capture whether the writer in the article can share pertinent information about the stock, sector, or style of investing. *ActionableScore* is designed to measure whether the article provides new information about a sector or security. *WellPresentedScore* measures whether the article is well written and leverages images, charts, and data sources to craft a logical, easy-to-understand investment thesis. *AggregateScore* is a composite of these three scores, among which the *ConvincingScore* is double weighted. These scores are available for 268 fake news articles and 91,365 legitimate news articles. The aggregate score and the component scores represent the SA editors' opinion about the underlying quality of an article. If an article does not report facts or real news, then it should be rated lower from an editorial point of view.

It is important to note that almost all articles that appear on Seeking Alpha are scored by editors. Between the start of editor scoring on June 20, 2012, and the end of our sample period on December 31, 2013, editors scored 96.94% of articles. The editor scoring overwhelmingly takes place before the article is published on SA. Only 0.58% of editor scoring takes place after the article was published. Thus, editors generally do not observe page views or other measures of attention when scoring the article.

3.4. Abnormal Returns and Abnormal Trading Volumes

We capture the market impact of a Seeking Alpha article by focusing on its primary ticker. To identify the main focus of an article, either the author or a Seeking Alpha editor tags an article with a primary stock ticker. When there is no primary ticker for an article, the article either does not cover any specific stock ticker or discusses several stock tickers all together. For all fake news articles, we consider the stock ticker identified by the SEC complaint as the primary ticker of an article. Twelve distinct stock tickers are associated with fake news articles. For legitimate news articles, we perform market reaction analysis only for the subsect of articles that contain a primary ticker.

Stock market data including prices, returns, and trading volumes are collected mainly from the Center for Research in Security Prices (CRSP). We require the firms to have a CRSP share code of 10 or 11. This excludes American Depositary Receipts (ADRs), shares of beneficial interest (SBIs), closed-end funds, and real estate investment trusts (REITS). Because the stocks covered by fake news articles are very small firms, the CRSP data are relatively more incomplete for such firms. We therefore supplement the CRSP data with manually collected data from Yahoo Finance and Google Finance for fake news articles. In total, we have abnormal returns data for 346 fake news articles and 51,051 legitimate news articles in our sample.

We use standard event study methods to estimate the excess return for firm i on day t as

$$ARet_{i,t} = Ret_{i,t} - Ret_{m,t},$$

where $ARet_{i,t}$ is the abnormal return, $Ret_{i,t}$ is the actual return, and $Ret_{m,t}$ is the return on the CRSP value-weighted index. We focus on market-adjusted returns so that we can have more observations for our analysis. We are interested in both short- and long-term market performances. The short-term performances are measured over the [0, +1] and [0, +2] windows. Long-term abnormal returns are measured over two windows: a six-month window from [+3, +120] and a one-year window from [+3, +242]. We also calculate the abnormal return over the period from [–30, –1] relative to the publication date to control for the run-up in the stock price prior to publication.

Finally, we also examine abnormal trading volume around the release of fake news. For each stock i, we calculate the abnormal trading volume on day t, $AVol_{i,t}$, as $(\frac{Vol_{i,t}}{\overline{Vol}_{i,t-5,t-65}})$, where $Vol_{i,t}$ is the trading volume on day t and $\overline{Vol}_{i,t-5,t-65}$ is the average trading volume over the $[t-5, t-65]$ window. We examine abnormal trading volumes over longer windows by cumulating the log of daily abnormal trading volumes. Similar to the abnormal return measure, we calculate abnormal trading volume over the [0, +1], [0, +2], [+3, +120], and [+3, +242] windows. In total, we have abnormal trading volumes data for 322 fake news articles and 49,900 legitimate news articles in our sample.

3.5. Firm Characteristics

For all articles that contain a primary ticker, we also consider the firm's characteristics including market capitalization (*Size*), market-to-book ratio (*Market-to-Book*), return on assets (*ROA*), and leverage (*LEV*). These variables are measured at the fiscal year end of the year prior to the article's publication. Compared with legitimate news articles, fake news stories tend to target small firms (based on market value). The size difference is quite large. The average market value of firms that are the subject of fake news stories is \$41.3 million, while for firms that are the subject of legitimate news articles it is \$57.7 billion. The average market capitalization of firms that are the subject of fake news articles would place them in the microcap universe of stocks. Fake news firms have a significantly lower profitability as measured by ROA and higher leverage than legitimate news firms.

3.6. Other Events

To account for the effects of other events on the various dependent variables, we also collect data on traditional media news, firms' earnings surprises, and financial analysts' upgrades and downgrades. For traditional media news, we use a firm's name as keyword to search in the Factiva database and manually download the English articles from all news media outlets covered by Factiva that mention the firm name during our study period. *%NegFactiva* is the average fraction of negative words across all Factiva news articles on the same day when the Seeking Alpha article was published (in percentage points). *Factiva* is a dummy variable denoting whether there is any Factiva news article published on the same day. *%NegFactiva* is zero when there is no Factiva news article published on the same day as the Seeking Alpha article. Because automatic downloading is prohibited by Factiva, we are only able to manually collect traditional media news data for a small sample of firms. For this reason, we focus on the firms covered by the matched sample of articles.

Firms' earnings surprises and financial analysts' upgrades and downgrades are constructed based on the data from the Institutional Brokers' Estimate System (IBES). Earnings surprise is defined as the difference between the actual earnings per share (EPS) reported by a firm and the average quarterly EPS forecast by financial analysts. *PosEA* is a dummy variable indicating whether there is a positive earnings surprise on the earnings announcement day, and *NegEA* is a dummy variable indicating whether there is a negative earnings surprise on the earnings announcement day. These two variables are zero when there is no earnings announcement. *Upgrade* and *Downgrade* are the number of recommendation upgrades and downgrades by financial analysts on a certain day.

4. Analyses and Results

Our analysis of fake news proceeds as follows. In Section 4.1, we identify a subset of legitimate news articles on firms with similar characteristics as those covered by fake news articles. In Sections 4.2–4.4, we compare fake news articles with a matched group of legitimate news articles in terms of investor attention and reactions from SA commenters and editors. In Section 4.5, we examine the ability of machine learning algorithms to detect fake news in financial markets based on linguistic characteristics. In Section 4.6, we examine the stock market reaction to fake news articles.

4.1. Propensity Score Matching

The summary statistics in Table 1 reveal that the sample of fake news articles identified by the SEC are different from the population of legitimate news articles in many aspects. Given that the fake news articles mainly target microcap firms, we first conduct propensity score matching (Rosenbaum and Rubin 1983, Dehejia and Wahba 2002, Caliendo and Kopeining 2008) to find a matched group of legitimate news articles that cover a set of firms similar as those targeted by fake news articles. For this purpose, we run a Probit regression on the full sample of both fake and legitimate news articles, for which we have all of the firm characteristics variables including *Size*, *Market-to-Ratio*, *ROA*, and *LEV*. These firm characteristics are measured as of the fiscal year end of the year prior to article publication. We also include the abnormal return over the previous 30 trading days prior to article publication, $ARet_{-30,-1}$, in the regression. Both sector and quarter dummies are included in the regression too so that the matched sample would be balanced in both industry sector and publication time. Table 2 presents the regression results of the Probit regression. Column (1) presents the

Table 2. Propensity Score Matching

Variables	(1) *Fake* before matching	(2) *Fake* after matching
Log*(Size)*	−0.818*** (0.045)	0.106 (0.083)
Market-to-Book	−0.001** (0.000)	0.000 (0.000)
ROA	0.085** (0.038)	0.053 (0.061)
LEV	0.051** (0.026)	0.015 (0.072)
$ARet_{-30,-1}$	−0.212** (0.089)	0.013 (0.119)
Constant	3.366*** (0.579)	−0.742 (0.818)
Sector fixed effect	Yes	Yes
Quarter fixed effect	Yes	Yes
Observations	14,518	496
Pseudo-R^2	0.616	0.018
Log-likelihood	−592.8	−337.6

Note. Standard errors are presented in parentheses.
** $p < 0.05$; *** $p < 0.01$.

full sample result. We find that market value, market-to-book ratio, and past return are negatively associated with the probability of being a fake news article, while return on assets and leverage are positively associated with the probability of being a fake news article.

We perform the one-on-one nearest-neighbor matching method to find a matched legitimate news article for each fake news article in our sample.[4] With a caliper of 0.02 and common support, we find a matched sample of 496 articles in total, among which 248 are fake news articles. Column (2) of Table 2 presents the result of the Probit regression on this matched sample. All the firm characteristics and past return are statistically insignificant at the 10% level, indicating that the firms covered by the matched legitimate news articles share similar characteristics as those of fake news articles. In the online appendix, we present the summary statistics for variables used in the matching procedure for the treatment and control groups separately and for both before- and after-matching.

4.2. Investor Attention Surrounding Fake News Articles

In this section, we examine investor attention to fake news articles relative to the matched group of legitimate news articles identified in Section 4.1. Before making the comparison in a regression framework, we first visually inspect and compare the trends of investor attention to these two types of articles over time. As mentioned in the data section, the attention data set we obtain from Seeking Alpha only covers part of the study period, so the number of articles used for this analysis is 172.

Figure 1 plots the mean of each of the four attention measures for fake and legitimate news for the first seven days after the release of the article. For all of these four attention measures (panels (A)–(D)), fake news stories generate higher levels of investor attention than legitimate news articles. The difference is particularly large in the first two days and dissipates quickly thereafter. In addition, the number of page views that also read the comments is on average quite small (less than a hundred) for both types of articles (panel (D)).

Next, we examine the investor attention of fake news articles in a regression framework. Table 3 presents the results of the regressions. The dependent variable is the log transformation of one of the four measures of overall attention after the release of the article.[5] *Fake* is the main independent variable of interest. We control for a host of article characteristics, other events, and firm characteristics. Controls for article characteristics include the article length (Log*(Length)*), fraction of negative words (%*NegWord*), whether the author received monetary payment from Seeking Alpha (*Premium*), whether the article was an editor pick (*EditorPick*), and the number of comments (Log*(Comment)*). Controls for other events include fraction of negative words in all Factiva news articles published on the same day (%*NegFactiva*), whether there was any Factiva news article published on the same day (*Factiva*), whether there was a positive earnings surprise (*PosEA*), and whether there was a negative earnings surprise (*NegEA*). We do not include controls for financial analysts' upgrades and downgrades as there was no such event for the firms covered by our matched sample of articles during the study period. Controls for firm characteristics include market value (*Size*), market to book ratio (*Market-to-Book*), return on assets (*ROA*), and leverage (*LEV*). The past return ($ARet_{-30,-1}$) is included, too. Both industry sector fixed effects and calendar quarter fixed effects are also included in the regressions.

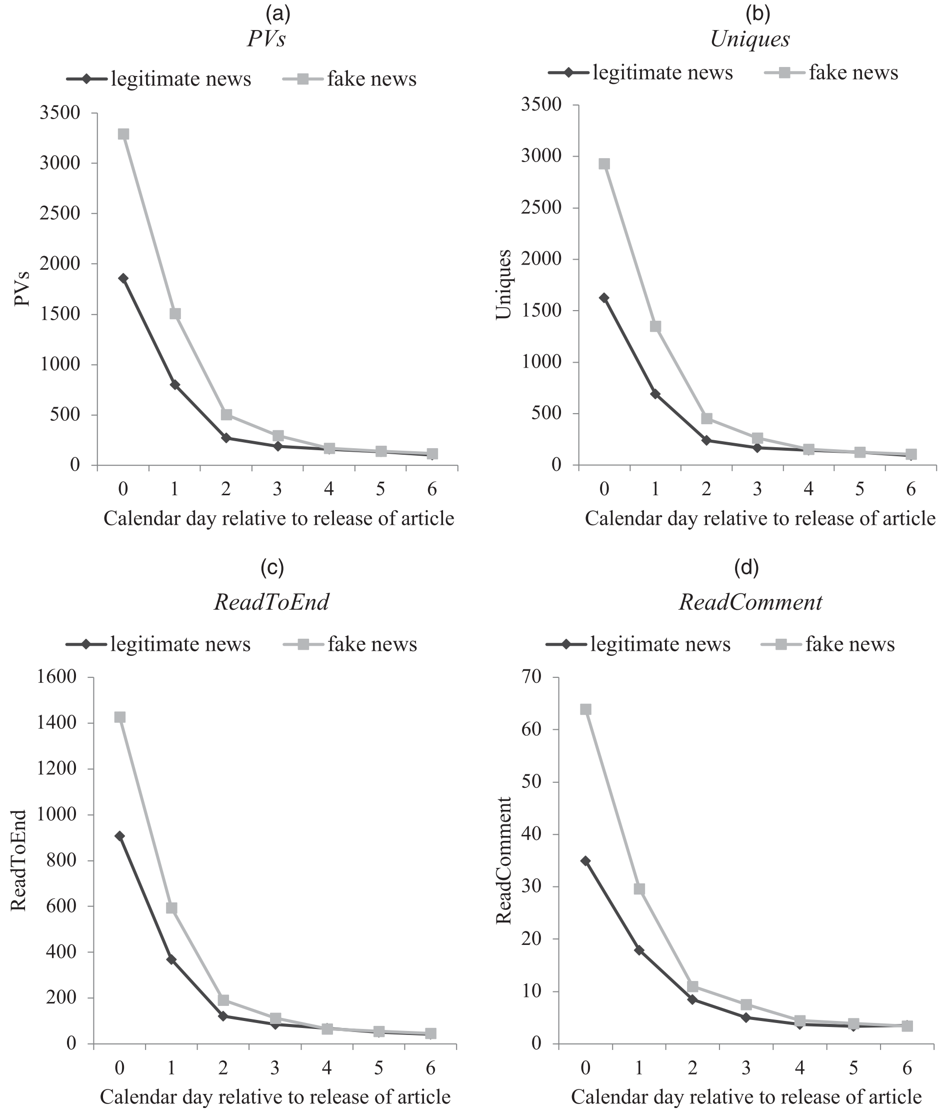
For the first three measures of investor attention, we find that fake news articles generate more investor attention than legitimate news stories. The coefficient on *Fake* is positive and statistically significant at the 1% level in columns (1)–(3) of Table 3. The results are also economically meaningful. For example, the coefficient on *Fake* in column (1) suggests that fake news articles on average generate 83.4% more page views than legitimate news articles. We find no statistically significant difference in the number of page views that also read article comments between fake news articles and legitimate news articles.[6]

Overall, the regression results are quite consistent with the insights revealed in Figure 1. Fake news is effective in capturing investor attention relative to a matched sample of legitimate news articles. These results provide strong support for our first hypothesis.

4.3. Commenter Reaction to Fake News

In this section, we examine whether and how individuals commenting on Seeking Alpha articles may

Figure 1. Investor Attention on Fake News



react differently to fake news. We regress *Comment* and %*Contradiction* on the *Fake* indicator variable and include the same set of controls as in Section 4.2.

The results are presented in Table 4. In column (1), the relation between the *Fake* indicator variable and *Comment* is insignificant. Thus, fake news articles do not generate a statistically different amount of comments than the matched sample of legitimate news articles. Together with the results for page views presented in the previous section, we can infer that fake news articles only attract more views but do not incite more discussions.

In column (2), we regress %*Contradiction* on the *Fake* news indicator and the same set of control variables as in column (1). If commenters were able to detect fake news, we would observe a higher level of disagreement between the sentiment by commenters and the sentiment revealed from the article. If commenters agreed more often with the article author for whatever reasons (e.g., commenters are hired by the author to promote the article by making comments, or commenters genuinely believe in the viewpoints shared by the author), then we would observe a lower level of disagreement or contradiction. The coefficient estimate on *Fake* in column (2) turns out to be statistically insignificant at the 10% level. This suggests that fake news articles generate neither more nor less contradiction in terms of sentiments revealed from the comments and the original article than the matched sample of legitimate news articles.

Overall, the results in Table 4 suggest that fake news articles do not generate more comments or more disagreement than legitimate news articles. This provides evidence consistent with Bond and DePaulo (2006) and Vrij (2008) that humans are not able to effectively detect deception.

Table 3. Investor Attention to Fake News

	(1)	(2)	(3)	(4)
Variables	Log(*PVs*)	Log(*Uniques*)	Log(*ReadToEnd*)	Log(*ReadComment*)
Fake	0.834*** (0.135)	0.855*** (0.132)	0.853*** (0.137)	–0.287 (0.387)
Log(*Length*)	0.198* (0.118)	0.196* (0.119)	–0.082 (0.125)	0.333 (0.315)
%NegWord	0.162* (0.095)	0.152 (0.099)	0.154 (0.102)	–0.051 (0.288)
Premium	–0.029 (0.102)	–0.021 (0.100)	0.003 (0.101)	–0.130 (0.304)
EditorPick	0.021 (0.172)	–0.040 (0.178)	–0.090 (0.193)	–1.130*** (0.383)
Log(*Comment*)	0.312*** (0.050)	0.301*** (0.050)	0.341*** (0.052)	0.434*** (0.133)
%NegFactiva	–0.046 (0.082)	–0.038 (0.081)	–0.033 (0.081)	0.004 (0.401)
Factiva	0.074 (0.107)	0.073 (0.106)	0.088 (0.113)	0.566 (0.346)
PosEA	–0.459** (0.233)	–0.458* (0.234)	–0.365 (0.244)	–0.778 (0.611)
NegEA	–0.045 (0.379)	–0.047 (0.390)	–0.009 (0.378)	–0.708 (0.863)
Log(*Size*)	0.056 (0.077)	0.067 (0.076)	0.070 (0.077)	–0.312* (0.190)
Market-to-Book	0.002*** (0.001)	0.002*** (0.001)	0.002** (0.001)	0.002 (0.002)
ROA	–0.143* (0.084)	–0.153* (0.084)	–0.146* (0.084)	0.412** (0.188)
LEV	–0.192*** (0.069)	–0.197*** (0.070)	–0.171** (0.068)	0.099 (0.148)
$ARet_{-30,-1}$	–0.019 (0.099)	–0.005 (0.101)	–0.030 (0.104)	–0.703** (0.313)
Constant	5.264*** (0.928)	5.167*** (0.929)	6.329*** (0.965)	–1.248 (2.428)
Sector fixed effect	Yes	Yes	Yes	Yes
Quarter fixed effect	Yes	Yes	Yes	Yes
Observations	172	172	172	172
Adjusted R^2	0.491	0495	0.475	0.426

Note. Robust standard errors are presented in parentheses.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

4.4. Editor Reaction to Fake News

We next examine whether Seeking Alpha editors score fake news articles lower than legitimate articles. Starting from June 20, 2012, editorial board at Seeking Alpha reviews all articles submitted to Seeking Alpha. Articles are given scores (on a scale of 1–4) along three dimensions: a *Convincing Score*, an *Actionable Score*, and a *Well-presented Score*. An *Aggregate Score* is computed as a composite of the three scores, where the *Convincing Score* receives double weight. In addition to these scores, we also track whether an article was an editor pick. According to Seeking Alpha, editor picks are highly discretionary and are based on the perceived timeliness and impact of the article.

Table 4. Commenter Reaction to Fake News

	(1)	(2)
Variables	*Comment*	*%Contradiction*
Fake	–3.621 (2.377)	–0.004 (0.059)
Log(*Length*)	9.103** (4.248)	–0.150** (0.064)
%NegWord	2.367* (1.328)	0.113* (0.061)
Premium	5.249*** (1.579)	0.225*** (0.058)
EditorPick	3.262 (4.605)	0.017 (0.110)
Log(*Comment*)		–0.158*** (0.035)
Log(*CommentWord*)		–0.098 (0.062)
%NegFactiva	1.207 (1.697)	–0.004 (0.082)
Factiva	2.650 (1.688)	0.096 (0.079)
PosEA	–15.219*** (3.675)	0.716*** (0.159)
NegEA	–10.387*** (3.111)	–0.249 (0.260)
Log(*Size*)	0.728 (0.971)	–0.012 (0.038)
Market-to-Book	0.003 (0.002)	0.000 (0.000)
ROA	–2.595 (1.759)	–0.021 (0.039)
LEV	–2.721 (1.692)	0.026 (0.036)
$ARet_{-30,-1}$	2.193 (2.097)	–0.019 (0.052)
Constant	–71.794** (33.733)	2.080*** (0.681)
Sector fixed effect	Yes	Yes
Quarter fixed effect	Yes	Yes
Observations	496	457
Adjusted R^2	0.133	0.094

Note. Robust standard errors are presented in parentheses.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 5 presents the regression results. In column (1), fake news articles are associated with an 8.1% lower likelihood of being an editor pick. Columns (2)–(4) show that the fake news indicator is negatively related to editor scores for convincing, actionable, and well presented. At first glance, the results appear to suggest that editors have an ability to discern fake news from legitimate news. However, the results are not economically meaningful, because scores are at most 0.172 points lower for fake news articles on a four-point scale. Column (5) examines the aggregate editor score. While the coefficient on the *Fake* indicator is also negative and statistically significant at the 1% level, the magnitude of the result is again not economically meaningful.

Overall, the evidence in Sections 4.3 and 4.4 suggests that neither editors nor commenters can reliably detect fake news. In the next section, we turn to machine learning techniques for detecting fake news articles.

Table 5. Editor Reaction to Fake News

	(1)	(2)	(3)	(4)	(5)
Variables	*EditorPick*	*Convincing Score*	*Actionable Score*	*WellPresented Score*	*Aggregate Score*
Fake	−0.081*** (0.030)	−0.172*** (0.044)	−0.165*** (0.052)	−0.102* (0.055)	−0.180*** (0.050)
Log(*Length*)	0.168*** (0.033)	0.296*** (0.046)	0.219*** (0.049)	0.205*** (0.055)	0.311*** (0.049)
%NegWord	0.032 (0.021)	0.059** (0.029)	−0.031 (0.035)	−0.014 (0.036)	0.037 (0.032)
Premium	−0.018 (0.026)	−0.035 (0.041)	−0.008 (0.046)	0.019 (0.051)	−0.033 (0.047)
Log(*Comment*)	−0.002 (0.014)	−0.007 (0.022)	0.025 (0.022)	−0.013 (0.026)	−0.014 (0.023)
%NegFactiva	−0.031 (0.021)	0.024 (0.047)	−0.094** (0.041)	−0.056 (0.043)	0.012 (0.052)
Factiva	0.004 (0.027)	0.001 (0.046)	0.082 (0.056)	0.009 (0.058)	0.028 (0.054)
PosEA	−0.155*** (0.059)	−0.165* (0.094)	−0.198* (0.111)	−0.210* (0.109)	−0.243** (0.100)
NegEA	−0.162*** (0.056)	0.011 (0.286)	−0.304*** (0.104)	0.059 (0.227)	−0.052 (0.303)
Log(*Size*)	0.015 (0.016)	0.009 (0.022)	−0.001 (0.031)	0.072** (0.034)	0.003 (0.028)
Market-to-Book	0.000 (0.000)	−0.001 (0.001)	0.000 (0.001)	0.001 (0.001)	−0.001 (0.001)
ROA	−0.006 (0.012)	0.012 (0.020)	0.004 (0.027)	−0.004 (0.027)	0.015 (0.021)
LEV	−0.011 (0.015)	0.010 (0.020)	−0.027 (0.021)	0.008 (0.026)	0.012 (0.021)
$ARet_{-30,-1}$	0.005 (0.020)	−0.028 (0.039)	−0.070 (0.044)	−0.019 (0.050)	−0.043 (0.047)
Constant	−1.316*** (0.269)	1.091** (0.493)	1.631*** (0.383)	1.950*** (0.512)	1.032** (0.515)
Sector fixed effect	Yes	Yes	Yes	Yes	Yes
Quarter fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	496	350	350	350	350
Adjusted R^2	0.104	0.151	0.046	0.061	0.110

Note. Robust standard errors are presented in parentheses.
$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

4.5. Detecting Fake News Based on Linguistic Characteristics

In this section, we explore whether it is feasible to detect fake news by conducting textual analysis and extracting features related with linguistic styles. Prior studies in the literature have shown the possibility of relying on linguistic styles to detect deception (e.g., Newman et al. 2003). We conjecture that the authors of fake news stories would make involuntarily different word choices than the authors of legitimate news stories despite the various efforts made by fake news stories' authors to disguise and hide their true intentions. We test this conjecture by analyzing the 93 output variables generated by the Linguistic Inquiry and Word Count (LIWC 2015) software (Pennebaker et al. 1993, 2015) for the matched sample of 248 fake news articles and 248 legitimate news articles. More specifically, we perform paired *t*-tests on the 93 output variables from LIWC 2015 and present the results in Table 6. We find that 65 out of these 93 linguistic characteristics are significantly different at the 5% level between fake news articles and legitimate news articles. This implies that linguistic styles can be potentially helpful in detecting fake news.

To further investigate how much linguistic styles can contribute to the detection of fake news, we implement six well-known classification algorithms including Gradient Boosting, Logistic Regression, Naïve Bayes, Neural Network, Random Forest, and Support Vector Machine based on the 93 output variables from the LIWC 2015 software. We write a Python program to run both training and testing. To utilize more training data, we focus on all fake news articles we have instead of the matched sample. Because the number of fake news articles in our sample is much smaller than the number of legitimate news article, we have the class imbalance problem. We adopt the following approach to address this problem. First, considering that most fake news articles (374 out of 383) either are about the healthcare sector or do not have a sector specified (i.e., null sector), we randomly select 374 articles from the population of legitimate news articles that have the same distribution in terms of industry sector as the fake news articles.[7] Second, together with the 374 fake news articles we have, we split the sample of 748 articles into a training data set and a testing data set with a ratio of 7:3. This way we ensure that both fake news and legitimate news articles are equally represented in the training and testing data sets. Third, we train a classifier based on one of the six classification algorithms mentioned above on the training data set and then perform prediction on the testing data set to obtain the performance measures such as precision, recall, and F1 score. Finally, to utilize more information about legitimate news articles that are available in our sample, we repeat the previous three steps 100 times and assess the prediction performances across these 100 experiments.

Table 7 summarizes the results of these 100 experiments for each of the six classification algorithms. We find that the gradient boosting classifier based on linguistic styles achieves the best performance among the six classifiers and is effective in detecting fake

Table 6. Linguistic Characteristics of Fake News

	Fake news (N = 248)		Legitimate news (N = 248)		*t*-test	
LIWC variables	Mean	Standard deviation	Mean	Standard deviation	*t*-stat	*p*-value
Word count	1,644.1	581.8	1,333.7	1,067.9	4.02	0.000
Analytical thinking	92.4	5.14	93.3	5.36	−1.85	0.065
Clout	50.5	6.13	54.5	8.50	−6.01	0.000
Authentic	29.1	11.9	28.5	14.2	0.47	0.639
Emotional tone	63.5	14.3	56.8	18.2	4.59	0.000
Words per sentence	25.2	3.73	22.7	3.93	7.31	0.000
Words>6 letters	27.9	3.40	27.7	3.69	0.36	0.718
Dictionary words	77.4	4.14	75.5	4.68	4.65	0.000
Function words	43.7	3.28	42.4	3.95	4.14	0.000
Total pronouns	6.41	1.78	6.39	1.97	0.15	0.884
Personal pronouns	1.40	0.84	2.05	1.22	−6.93	0.000
First-person singular	0.74	0.53	0.91	0.75	−2.93	0.004
First-person plural	0.23	0.30	0.48	0.67	−5.30	0.000
Second person	0.14	0.26	0.16	0.27	−0.69	0.493
Third-person singular	0.054	0.11	0.11	0.27	−2.91	0.004
Third-person plural	0.24	0.26	0.40	0.41	−5.28	0.000
Impersonal pronouns	5.01	1.31	4.34	1.31	5.74	0.000
Articles	8.55	1.12	8.09	1.24	4.31	0.000
Prepositions	14.7	1.20	14.9	1.33	−2.07	0.039
Auxiliary verbs	6.88	1.24	6.53	1.47	2.88	0.004
Common adverbs	3.10	0.88	2.76	1.07	3.87	0.000
Conjunctions	5.35	0.84	4.66	0.90	8.83	0.000
Negations	0.71	0.33	0.86	0.42	−4.18	0.000
Regular verbs	10.4	1.77	10.0	2.21	2.11	0.035
Adjectives	5.09	0.95	4.61	1.02	5.44	0.000
Comparatives	2.91	0.71	2.55	0.77	5.48	0.000
Interrogatives	0.87	0.34	0.90	0.44	−0.93	0.354
Numbers	4.04	1.63	4.86	2.31	−4.56	0.000
Quantifiers	2.26	0.56	2.05	0.61	3.97	0.000
Affect words	4.01	0.74	3.96	1.03	0.52	0.605
Positive emotion	3.01	0.63	2.81	0.80	3.12	0.002
Negative emotion	0.97	0.44	1.12	0.64	−3.15	0.002
Anxiety	0.21	0.17	0.29	0.25	−3.87	0.000
Anger	0.20	0.18	0.15	0.20	2.71	0.007
Sadness	0.31	0.25	0.34	0.26	−1.12	0.262
Social words	3.53	1.09	4.37	1.40	−7.54	0.000
Family	0.010	0.031	0.020	0.059	−2.15	0.032
Friends	0.12	0.18	0.15	0.18	−2.32	0.021
Female referents	0.038	0.11	0.039	0.13	−0.10	0.923
Male referents	0.047	0.11	0.13	0.30	−4.16	0.000
Cognitive processes	10.1	1.86	9.43	1.83	3.88	0.000
Insight	1.88	0.64	1.85	0.70	0.56	0.577
Cause	2.47	0.69	2.30	0.71	2.59	0.010
Discrepancies	1.29	0.46	1.14	0.54	3.45	0.001
Tentativeness	2.41	0.64	2.24	0.78	2.71	0.007
Certainty	1.03	0.40	0.97	0.44	1.43	0.154
Differentiation	2.32	0.73	2.06	0.71	3.88	0.000
Perceptual processes	1.07	0.45	1.14	0.61	−1.54	0.125
Seeing	0.64	0.31	0.59	0.36	1.41	0.159
Hearing	0.13	0.13	0.17	0.21	−2.42	0.016
Feeling	0.18	0.17	0.28	0.36	−3.79	0.000
Biological processes	3.71	1.77	3.15	1.94	3.31	0.001
Body	0.59	0.46	0.52	0.58	1.53	0.128
Health/illness	2.92	1.53	2.48	1.66	3.07	0.002
Sexuality	0.16	0.28	0.089	0.22	3.20	0.001
Ingesting	0.22	0.53	0.19	0.26	0.70	0.484
Drives and needs	6.68	1.08	7.06	1.56	−3.16	0.002
Affiliation	0.83	0.49	1.34	0.78	−8.71	0.000
Achievement	2.36	0.70	1.97	0.65	6.44	0.000
Power	2.69	0.65	2.83	0.91	−2.05	0.041
Reward focus	1.57	0.51	1.26	0.56	6.41	0.000

Table 6. (Continued)

	Fake news (N = 248)		Legitimate news (N = 248)		t-test	
LIWC variables	Mean	Standard deviation	Mean	Standard deviation	t-stat	p-value
Risk focus	0.56	0.32	0.67	0.43	–3.42	0.001
Past focus	2.12	0.74	2.21	0.95	–1.28	0.202
Present focus	7.12	1.37	7.21	1.75	–0.67	0.503
Future focus	1.68	0.50	1.45	0.61	4.68	0.000
Relativity	13.9	2.06	13.8	2.41	0.68	0.496
Motion	1.72	0.59	1.68	0.62	0.63	0.529
Space	7.01	0.97	7.24	1.38	–2.16	0.031
Time	5.40	1.31	5.08	1.39	2.65	0.008
Work	6.32	1.57	5.97	1.58	2.46	0.014
Leisure	0.38	0.29	0.35	0.27	1.32	0.187
Home	0.040	0.061	0.066	0.10	–3.46	0.001
Money	2.79	1.20	3.30	1.73	–3.82	0.000
Religion	0.044	0.16	0.022	0.057	2.05	0.041
Death	0.066	0.093	0.061	0.11	0.59	0.558
Informal speech	0.15	0.13	0.29	0.29	–6.79	0.000
Swear words	0.00028	0.0044	0.0098	0.098	–1.53	0.127
Netspeak	0.029	0.071	0.14	0.26	–6.39	0.000
Assent	0.015	0.035	0.035	0.074	–3.85	0.000
Nonfluencies	0.11	0.11	0.14	0.15	–2.27	0.024
Fillers	0.00016	0.0025	0	0	1.00	0.318
All punctuation	15.7	2.22	16.7	2.94	–4.48	0.000
Periods	4.26	0.59	4.78	0.83	–8.09	0.000
Commas	4.90	1.17	4.40	1.29	4.49	0.000
Colons	0.20	0.14	0.42	0.37	–8.63	0.000
Semicolons	0.086	0.11	0.075	0.14	1.01	0.313
Question marks	0.068	0.13	0.10	0.21	–2.05	0.041
Exclamation marks	0.0096	0.034	0.017	0.10	–1.08	0.280
Dashes	1.50	0.68	1.55	0.91	–0.70	0.484
Quotation marks	0.37	0.39	0.40	0.50	–0.61	0.545
Apostrophes	1.09	0.43	1.06	0.67	0.54	0.589
Parentheses (pairs)	1.59	0.75	1.99	1.20	–4.34	0.000
Other punctuation	1.58	0.83	1.91	1.36	–3.32	0.001

news stories. On average, this classifier has achieved a precision of 87.1%, a recall of 90.5%, and an F1 score of 88.7%. We also find that logistic regression and random forest achieve very good performances (e.g., an F1 score of above 87%) but that the naïve Bayes classifier performs the worst, delivering an F1 score of only 73.4%. While neither commenters nor editors are able to reliably identify fake news, our results from machine learning and textual analysis imply that linguistic styles can be particularly informative in detecting fake news. We acknowledge that one challenge to implement such machine learning techniques in practice is the lack of sufficient and accurate data on fake news.

To identify the most important linguistic characteristics that contribute to the detection of fake news articles, we employ the XGBoost package (Chen and Guestrin 2016), which is one of the most popular implementations of the gradient boosting algorithm, to generate the feature importance scores for the 93 LIWC linguistic features.[8] Given the small number of fake news articles in our sample, we calculate the average feature importance scores across the 100 random experiments described above. Table 8 presents the top 30 most important features and their average scores identified by XGBoost. Note that the expected feature importance score would be 1.08% (= 100/93), if each of the 93 features contributes equally. We find that Word Count and Words per Sentence are two of the most important feature components. These findings are consistent with the finding of Zhou and Zhang (2008) that liars use more words and more words per sentence to appear more persuasive and credible. Fake news articles tend to have fewer references to money and numbers than legitimate news articles. This is consistent with Larcker and Zakolyukina (2012), who find that deceptive CEOs use significantly fewer words associated with value. First-person plural words is also a key linguistic feature. This is consistent with Zhou et al. (2004), who find that deceivers use less first-person plural words (i.e., group references) than truth tellers.

Table 7. Performance of Six Machine Learning Algorithms for Detecting Fake News

Measure	Median	Mean	Standard deviation	Minimum	Maximum
			Panel A: Gradient boosting		
Precision	0.871	0.871	0.031	0.769	0.939
Recall	0.907	0.905	0.027	0.833	0.981
F1	0.889	0.887	0.018	0.834	0.936
			Panel B: Logistic regression		
Precision	0.857	0.852	0.032	0.765	0.928
Recall	0.900	0.897	0.033	0.804	0.962
F1	0.873	0.873	0.024	0.814	0.932
			Panel C: Naïve Bayes		
Precision	0.756	0.756	0.037	0.672	0.844
Recall	0.716	0.715	0.049	0.606	0.825
F1	0.731	0.734	0.033	0.652	0.818
			Panel D: Neural network		
Precision	0.848	0.839	0.070	0.654	0.974
Recall	0.918	0.864	0.123	0.436	0.991
F1	0.855	0.842	0.056	0.596	0.935
			Panel E: Random forest		
Precision	0.883	0.883	0.030	0.804	0.955
Recall	0.880	0.880	0.030	0.804	0.957
F1	0.881	0.881	0.019	0.839	0.927
			Panel F: Support vector machine		
Precision	0.835	0.834	0.033	0.750	0.933
Recall	0.873	0.868	0.036	0.750	0.933
F1	0.848	0.850	0.024	0.785	0.905

Note. Results for each machine learning algorithm are based on 100 experiments.

In sum, the results in this section are consistent with our second hypothesis and show that linguistic features are useful for detecting fake news articles. Many of the same linguistic features that are useful for detecting deception in other settings also prove useful for detecting fake news.

4.6. Market Reaction to Fake News

In this section, we examine the stock price and volume reaction to fake news articles. As a first pass, we examine the abnormal trading volume surrounding the release of fake news. We compare the abnormal trading volumes associated with fake and legitimate news on each day over the window [0, +5], where day 0 corresponds to the Seeking Alpha publication date. The results are presented in Figure 2. Fake news articles generate statistically significant abnormal trading volume on day 0, as abnormal trading volume is larger than 1. Thus, the release of fake news is not a "non-event." However, abnormal trading volume is significantly less than observed for legitimate news articles. This finding is consistent with our third hypothesis.

In Table 9, we examine the abnormal volume reaction in a regression framework. We consider the log of abnormal volume over four windows: [0, +1], [0, +2], [+3, +120], and [+3, +242]. We again control for article characteristics, other events, and firm characteristics, and include sector and quarter fixed effects. Across all four specifications, we find a negative and significant coefficient estimate on *Fake*, suggesting that fake news stories induce a lower trading volume reaction than legitimate news stories. This finding is consistent with Hypothesis 3.

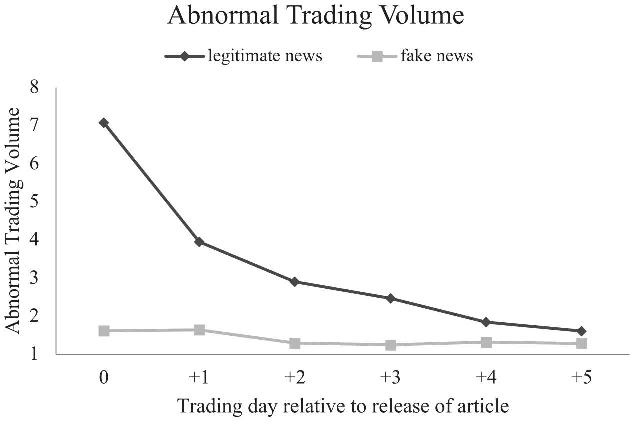
To examine the information content of the stock market response to fake news, we focus on the absolute value of the abnormal returns over the same four windows: [0, +1], [0, +2], [+3, +120], and [+3, +242] in Table 10. For the latter two long-term return windows, we control for the initial market reaction. In all columns, we control for article characteristics, other events, and firm characteristics and include sector and quarter fixed effects. The key variable of interest is the *Fake* indicator. Across all four specifications, the coefficient estimate on *Fake* is negative and statistically significant. Thus, the magnitude of

Table 8. Top 30 Most Important Linguistic Features for Fake News Detection

Feature	Examples	Importance
Word count	—	6.96%
Colons	—	3.81%
Money	audit, cash, owe	3.50%
Words per sentence	—	2.81%
First-person plural	we, us, our	2.56%
Biological processes	eat, blood, pain	2.52%
Periods	—	2.47%
Netspeak	btw, lol, thx	2.20%
Personal pronouns	I, them, her	2.11%
All punctuation	—	1.97%
Numbers	—	1.93%
Reward focus	take, prize, benefit	1.87%
Sexuality	horny, love, incest	1.86%
Conjunctions	and, but, whereas	1.69%
Achievement	win, success, better	1.64%
Emotional tone	score (0 to 100) for positive vs. negative emotion	1.57%
Function words	it, to, no, very	1.57%
Parentheses (pairs)	—	1.56%
Affiliation	ally, friend, social	1.53%
Future focus	may, will, soon	1.49%
Health/illness	clinic, flu, pill	1.48%
Impersonal pronouns	it, it's, those	1.45%
Informal speech	damn, hm, OK	1.44%
Body	cheek, hands, spit	1.42%
Social words	mate, talk, they	1.39%
Risk focus	danger, doubt	1.37%
Negations	no, not, never	1.36%
Negative emotion	hurt, ugly, nasty	1.35%
Articles	a, an, the	1.31%
Clout	score (0 to 100) for social status, confidence, or leadership	1.23%

the stock price reaction to fake news articles is less than that of legitimate news articles. The result is economically meaningful. The coefficient on *Fake* in column (2), for example, indicates that the magnitude of the response to fake news articles from day 0 to +2 is 2.5% lower than that of legitimate news articles. This result is consistent with Hypothesis 4. In sum, the results in Tables 9 and 10 suggest that the market discounts the release of fake news.

Figure 2. Abnormal Volume Reaction to Fake News



5. Conclusion

This paper examines investor attention and the stock price reaction to articles identified by the SEC as fake news. The vast majority of articles identified by the SEC as fake news appeared on the website Seeking Alpha, which allows us to examine whether the fake news captured investor attention and whether it impacted stock prices.

We find that investor attention, as measured by page views and the number of times an article was read to the end, is significantly higher for fake news articles than a matched control sample of legitimate news articles. The results are both economically and statistically significant. Fake news articles generate about 83.4% more page views than a matched sample of legitimate articles.

We find little evidence that article commenters or Seeking Alpha editors can successfully identify fake news articles. Therefore, we explore whether machine learning techniques can reliably be used to identify fake news articles. Through a textual analysis of both fake news articles and legitimate news articles that specifically looks at linguistic styles, we find that fake news articles differ from legitimate news articles in word choices. We then implement

Table 9. Market Reaction to Fake News—Trading Volume

	(1)	(2)	(3)	(4)
Variables	Log($AVol_{0,1}$)	Log($AVol_{0,2}$)	Log($AVol_{3,120}$)	Log($AVol_{3,242}$)
Fake	−0.408*** (0.080)	−0.421*** (0.081)	−0.055* (0.029)	−0.079*** (0.021)
Log($AVol_{0,2}$)			0.030 (0.018)	0.026* (0.015)
Log(*Length*)	0.008 (0.094)	0.029 (0.096)	0.052* (0.031)	−0.009 (0.024)
%NegWord	−0.055 (0.054)	−0.071 (0.053)	−0.033 (0.020)	0.019 (0.019)
Premium	−0.003 (0.076)	0.017 (0.078)	−0.055** (0.028)	−0.027 (0.022)
EditorPick	0.100 (0.154)	0.055 (0.161)	−0.001 (0.047)	−0.023 (0.033)
Log(*Comment*)	0.056 (0.037)	0.067* (0.038)	−0.015 (0.012)	−0.016 (0.010)
%NegFactiva	−0.037 (0.080)	−0.044 (0.083)	0.019 (0.023)	−0.004 (0.018)
Factiva	0.214** (0.104)	0.182* (0.104)	−0.082*** (0.031)	−0.039 (0.027)
PosEA	0.025 (0.209)	−0.194 (0.209)	0.041 (0.075)	−0.245*** (0.093)
NegEA	−0.382*** (0.123)	−0.462*** (0.132)	0.072* (0.040)	−0.100 (0.113)
Log(*Size*)	−0.033 (0.061)	−0.025 (0.062)	0.020 (0.021)	−0.027 (0.018)
Market-to-Book	0.000 (0.000)	0.000* (0.000)	0.000 (0.000)	0.000*** (0.000)
ROA	0.046 (0.043)	0.047 (0.045)	−0.028 (0.019)	−0.002 (0.020)
LEV	0.070 (0.053)	0.070 (0.057)	−0.068** (0.027)	−0.030 (0.022)
$ARet_{-30,-1}$	0.337*** (0.119)	0.336*** (0.114)	−0.074** (0.029)	−0.062*** (0.022)
Constant	1.449 (0.913)	1.472 (0.931)	4.529*** (0.285)	5.675*** (0.245)
Sector fixed effect	Yes	Yes	Yes	Yes
Quarter fixed effect	Yes	Yes	Yes	Yes
Observations	496	496	496	496
Adjusted R^2	0.116	0.118	0.129	0.125

Note. Robust standard errors are presented in parentheses.
$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

six well-known classification algorithms including Gradient Boosting, Logistic Regression, Naïve Bayes, Neural Network, Random Forest, and Support Vector Machine based on the LIWC linguistic features. The gradient boosting classifier achieves the highest average F1 score of 88.7%. Overall, these results suggest that linguistic styles are informative for detecting fake news.

Table 10. Market Reaction to Fake News—|Abnormal Return|

	(1)	(2)	(3)	(4)
Variables	$\lvert ARet_{0,1}\rvert$	$\lvert ARet_{0,2}\rvert$	$\lvert ARet_{3,120}\rvert$	$\lvert ARet_{3,242}\rvert$
Fake	−0.018* (0.010)	−0.025** (0.010)	−0.104** (0.042)	−0.204*** (0.050)
$\lvert ARet_{0,2}\rvert$			0.442*** (0.157)	0.161 (0.214)
Log(*Length*)	0.004 (0.013)	0.017 (0.012)	0.016 (0.037)	0.006 (0.054)
%NegWord	0.010 (0.007)	0.009 (0.007)	−0.012 (0.027)	−0.047 (0.034)
Premium	0.020* (0.010)	0.015 (0.010)	−0.040 (0.041)	0.040 (0.056)
EditorPick	−0.016 (0.017)	−0.013 (0.017)	0.049 (0.065)	−0.033 (0.073)
Log(*Comment*)	0.007* (0.004)	0.011*** (0.004)	0.028 (0.021)	0.030 (0.028)
%NegFactiva	0.003 (0.010)	0.002 (0.010)	−0.042 (0.027)	−0.065* (0.039)
Factiva	0.007 (0.005)	0.006 (0.004)	0.002 (0.007)	−0.016** (0.007)
PosEA	0.004 (0.028)	0.018 (0.025)	−0.063 (0.086)	0.022 (0.098)
NegEA	−0.071*** (0.025)	−0.071*** (0.018)	0.028 (0.102)	−0.143 (0.126)
Log(*Size*)	0.008 (0.011)	−0.001 (0.009)	0.034 (0.028)	0.015 (0.039)
Market-to-Book	0.000** (0.000)	0.000 (0.000)	0.000** (0.000)	0.000 (0.000)
ROA	−0.001 (0.004)	−0.001 (0.005)	−0.007 (0.021)	0.009 (0.023)
LEV	−0.001 (0.005)	−0.002 (0.005)	0.002 (0.030)	−0.018 (0.032)
$ARet_{-30,-1}$	0.021** (0.010)	0.011 (0.009)	−0.010 (0.037)	0.006 (0.041)
Constant	−0.066 (0.130)	−0.100 (0.113)	0.196 (0.304)	0.642 (0.447)
Sector fixed effect	Yes	Yes	Yes	Yes
Quarter fixed effect	Yes	Yes	Yes	Yes
Observations	496	496	496	496
Adjusted R^2	0.039	0.038	0.073	0.069

Note. Robust standard errors are presented in parentheses.
$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Both the abnormal volume reaction and the magnitude of the abnormal return response to fake news articles are significantly less than that of a matched sample of legitimate news articles. Taken together, the abnormal volume and absolute abnormal return results suggest that the market appears to discount for fake news articles. Given the proliferation of fake news articles on social media and the attempts to use fake news to influence everything from stock prices to political elections, we believe these results have widespread implications.

It is worth noting some limitations to our study. Our study is limited to cases where the SEC brought an enforcement action. We do not observe cases where either (1) fake news occurs but is not detected or (2) fake news is detected but the SEC does not bring an enforcement action. Our sample of fake news articles is relatively small and also skewed heavily toward microcap stocks. Thus, we cannot easily address whether fake news can be used to manipulate stock prices for large companies that likely have significant institutional and analyst following. We leave these topics for future work.

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Endnotes

[1] Our sample of fake news articles is available upon request.

[2] A copy of this list is available at https://ftalphaville-cdn.ft.com/wp-content/uploads/2017/04/10231526/Stock-promoters.pdf. Accessed May 24, 2018.

[3] The contents of these 383 fake news articles and their comments can be obtained from the authors for academic research purposes.

[4] In addition to nearest-neighbor matching, we also use both radius and kernel matching. Our results under these alternative matching approaches are consistent with the results for nearest-neighbor matching and available upon request.

[5] Our results remain qualitatively the same when the attention variables are measured over a specific time window—e.g., the first seven days after article publication.

[6] In the online appendix, we conduct a robustness test by regressing on a dummy variable, *ReadCommentDummy*, which denotes whether an article has its comments read by at least one visitor. Our result continues to hold. There are two possible and not necessarily exclusive explanations for this result. The first explanation is that the number of page views that also read comments is essentially measuring the attention to the comments of articles. In the next subsection, we show that commenter reactions to fake news and legitimate news articles are quite similar (Table 4). Together with these results, it is reasonable to expect that investor attention to comments on these two types of articles would be similar, too. In other words, investor attention to fake news is higher, but investor attention to real comments on fake news does not differ. The second explanation is that fake news articles attract more page views than legitimate news articles, but that after they read the articles, investors may not find them as interesting as expected and thus do not make more comments or read the comments more.

[7] Without the industry sector restriction in the sampling process, we would potentially have an overfitting problem. Words related to the healthcare sector would be considered more important in detecting fake news as the proportion of legitimate news articles in the healthcare sector is much smaller than that of fake news articles.

[8] The results are similar when other gradient boosting algorithms are used to generate the feature importance scores.

References

Agrawal A, Chen MA (2008) Do analyst conflicts matter? Evidence from stock recommendations. *J. Law Econom.* 51(3):503–537.

Allcott H, Gentzkow M (2017) Social media and fake news in the 2016 election. *J. Econom. Perspect.* 31(2):211–236.

Bamber L, Cheon Y (1995) Differential price and volume reactions to accounting earnings announcements. *Accounting Rev.* 70(3): 417–441.

Bond CF, DePaulo BM (2006) Accuracy of deception judgments. *Personality Soc. Psych. Rev.* 10(3):214–234.

Brunnermeier M, Parker J (2005) Optimal expectations. *Amer. Econom. Rev.* 95(4):1092–1118.

Bushee B, Core J, Guay W, Hamm S (2010) The role of the business press as an information intermediary. *J. Accounting Res.* 48(1): 1–19.

Caliendo M, Kopeining S (2008) Some practical guidance for the implementation of propensity score matching. *J. Econom. Survey* 22(1):31–72.

Chen T, Guestrin C (2016) XGBoost: A scalable tree boosting system. *Proc. 22nd ACM SIGKDD Internat. Conf. Knowledge Discovery Data Mining* (ACM, New York), 785–794.

Chen H, De P, Hu Y, Hwang B (2014) Wisdom of crowds: The value of stock opinions transmitted through social media. *Rev. Financial Stud.* 27:1367–1403.

Cheon Y, Christensen T, Bamber L (2001) Factors associated with differences in the magnitude of abnormal returns around NYSE vs. Nasdaq firms' earnings announcements. *J. Bus. Finance Accounting* 28(9–10):1073–1108.

Chopra F, Haaland I, Roth C (2019) Do people value more informative news? Working paper, University of Warwick, Warwick, UK.

Dehejia RH, Wahba S (2002) Propensity score-matching methods for nonexperimental causal studies. *Rev. Econom. Statist.* 84(1):151–161.

Golman R, Hagmann D, Loewenstein G (2017) Information avoidance. *J. Econom. Lit.* 55(1):96–135.

Hobson J, Mayew W, Venkatachalam M (2011) Analyzing speech to detect financial misreporting. *J. Accounting Res.* 50(2):349–392.

Hu N, Bose I, Koh NS, Liu L (2012) Manipulation of online reviews: An analysis of ratings, readability, and sentiments. *Decision Support Systems* 52(3):674–684.

Isaac M, Wakabayashi D (2017) Russian influence reached 126 million through Facebook alone. *New York Times* (October 30), https://www.nytimes.com/2017/10/30/technology/facebook-google-russia.html.

Kim O, Verrecchia R (1991) Trading volume and price reactions to public announcements. *J. Accounting Res.* 29(2):302–321.

Kirk M (2011) Research for sale: Determinants and consequences of paid-for analyst research. *J. Financial Econom.* 100(1):182–200.

Kogan S, Moskowitz TJ, Niessner M (2019) Fake news: Evidence from financial markets. Working paper, Massachusetts Institute of Technology, Cambridge, MA.

Lappas T, Sabnis G, Valkanas G (2016) The impact of fake reviews on online visibility: A vulnerability assessment of the hotel industry. *Inform. Systems Res.* 27(4):940–961.

Larcker D, Zakolyukina A (2012) Detecting deceptive discussions in conference calls. *J. Accounting Res.* 50(2):495–540.

Loughran T, McDonald B (2011) When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *J. Finance* 66(1):35–65.

Luca M, Zervas G (2016) Fake it till you make it: Reputation, competition, and Yelp review fraud. *Management Sci.* 62(12): 3412–3427.

Newman M, Pennebaker J, Berry D, Richards J (2003) Lying words: Predicting deception from linguistic styles. *Personality Soc. Psych. Bull.* 29(5):665–675.

Pennebaker JW, Francis ME, Booth RJ (1993) Linguistic inquiry and word count. Technical report, Southern Methodist University, Dallas.

Pennebaker JW, Booth RJ, Boyd RL, Francis ME (2015) *Linguistic Inquiry and Word Count: LIWC2015* (Pennebaker Conglomerates, Austin, TX).

Purda L, Skillicorn D (2014) Accounting variables, deception, and a bag of words: Assessing the tools of fraud detection. *Contemporary Accounting Res.* 32(3):1193–1223.

Rosenbaum PR, Rubin DB (1983) The central role of the propensity score in observational studies for causal effects. *Biometrika* 70(1):41–55.

Stempel J (2017) SEC targets fake stock news on financial websites. *Reuters* (April 10), https://www.reuters.com/article/us-sec-fakenews-idUSKBN17C1YP.

Tetlock PC (2007) Giving content to investor sentiment: The role of media in the stock market. *J. Finance* 62(3):1139–1168.

Tetlock P, Saar-Tsechansky M, Macskassy S (2008) More than words: Quantifying language to measure firms' fundamentals. *J. Finance* 63(3):1437–1467.

U.S. Securities and Exchange Commission (2017) SEC: Payments for bullish articles on stocks must be disclosed to investors. Accessed January 6, 2020, https://www.sec.gov/news/press-release/2017-79.

Vosoughi S, Roy D, Aral S (2018) The spread of true and false news online. *Science* 359(6380):1145–1151.

Vrij A (2008) *Detecting Lies and Deceit: Pitfalls and Opportunities*, 2nd ed. (Wiley-Interscience, New York).

Zhou L, Zhang D (2008) Following linguistic footprints: Automatic deception detection in online communication. *Comm. ACM* 51(9):119–122.

Zhou L, Burgoon JK, Nunamaker JF, Twitchell D (2004) Automating linguistics-based cues for detecting deception in text-based asynchronous computer-mediated communication. *Group Decision Negotiation* 13(1):81–106.